Renewable and Sustainable Energy Reviews 13 (2009) 1819–1835

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Modeling of end-use energy consumption in the residential sector: A review of modeling techniques

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A R T I C L E I N F O

Article history:
Received 9 September 2008
Accepted 30 September 2008

Keywords:
Residential energy model
Residential energy consumption
Housing energy model
Energy model

A B S T R A C T

There is a growing interest in reducing energy consumption and the associated greenhouse gas emissions in every sector of the economy. The residential sector is a substantial consumer of energy in every country, and therefore a focus for energy consumption efforts. Since the energy consumption characteristics of the residential sector are complex and inter-related, comprehensive models are needed to assess the technoeconomic impacts of adopting energy efficiency and renewable energy technologies suitable for residential applications.

The aim of this paper is to provide an up-to-date review of the various modeling techniques used for modeling residential sector energy consumption. Two distinct approaches are identified: top-down and bottom-up. The top-down approach treats the residential sector as an energy sink and is not concerned with individual end-uses. It utilizes historic aggregate energy values and regresses the energy consumption of the housing stock as a function of top-level variables such as macroeconomic indicators (e.g. gross domestic product, unemployment, and inflation), energy price, and general climate. The bottom-up approach extrapolates the estimated energy consumption of a representative set of individual houses to regional and national levels, and consists of two distinct methodologies: the statistical method and the engineering method.

Each technique relies on different levels of input information, different calculation or simulation techniques, and provides results with different applicability. A critical review of each technique, focusing on the strengths, shortcomings and purposes, is provided along with a review of models reported in the literature.

Contents

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doi:10.1016/j.rser.2008.09.033

Nomenclature

Acronyms

AEEI	autonomous energy efficiency index
AL	appliances and lighting
ALC	appliances, lighting and cooling
ASHRAE	American Society of Heating, Refrigeration and Air-conditioning Engineers
BEAM	Built Environment Analysis Model
CBECS	Commercial Buildings Energy Consumption Survey
CDA	conditional demand analysis
DHW	domestic hot water
EM	engineering method
EPI	energy performance index
GA	genetic algorithm
GDP	gross domestic product
GIS	geographical information systems
HAP	Hourly Analysis Program
HDD	heating degree days
NEMS	National Energy Modeling System
NN	neural network
SC	space cooling
SH	space heating
SM	statistical method
UEC	unit energy consumption

Symbols

b	constant
B	billing data
c	coefficient
C	appliance ownership (presence or count)
E	energy consumption
HDD	heating degree days
I	income
Pc	price
R	appliance rating
R^2	multiple correlation coefficient
S	housing stock
T	temperature
U	use factor
V	array of interaction variables

Subscripts

an	annual
app	appliance
dis	disposable
e	end-use group
f	fuel type
i	array element location
mo	monthly
ref	reference
t	time or period of time

1. Introduction

Nationally, energy consumption of the residential sector accounts for 16–50% of that consumed by all sectors, and averages approximately 30% worldwide as shown in Fig. 1. This significant consumption level warrants a detailed understanding of the residential sector's consumption characteristics to prepare for and help guide the sector's energy consumption in an increasingly energy conscience world; conscience from standpoints of supply, efficient use, and effects of consumption. In response to climate change, high energy prices, and energy supply/demand, there is interest in understanding the detailed consumption characteristics of the residential sector in an effort to promote conservation, efficiency, technology implementation and energy source switching, such as to on-site renewable energy.

Energy consumption of other major sectors such as commercial, industrial, agriculture and transportation are better understood than the residential sector due to their more centralized ownership, self-interest and expertise in reducing energy consumption, and high levels of regulation and documentation. The residential sector is largely an undefined energy sink due to the following reasons:

- The sector encompasses a wide variety of structure sizes, geometries and thermal envelope materials.
- Occupant behaviour varies widely and can impact energy consumption by as much as 100% for a given dwelling [2].
- Privacy issues limit the successful collection or distribution of energy data related to individual households.
- Detailed sub-metering of household end-uses has prohibitive cost.

The residential sector consumes secondary energy. Secondary energy is that received in suitable form for use by the consuming systems to support the living standards of occupants. The major end-use groups of secondary energy are:

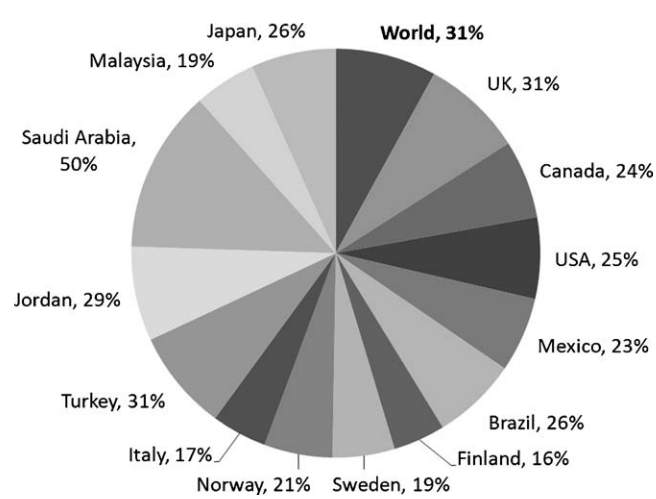

Fig. 1. Residential energy consumption shown as a percentage of national energy consumption and in relative international form [1].

- Space heating (SH) and space cooling (SC)—energy required to support thermal losses incurred across the building envelope due to conduction and radiation, as well as air infiltration/ventilation in an effort to maintain the living space at a comfortable temperature and air quality.
- Domestic hot water (DHW)—energy required to heat water to a comfortable or appropriate temperature for occupant and appliance uses.
- Appliances and lighting (AL)—energy consumed to operate common appliances (e.g. refrigerator and coffee maker) and for the provision of adequate lighting.

The degree to which these groups affect the overall energy consumption is highly dependent on climate, physical dwelling characteristics, appliance and system characteristics, ownership, and occupant behaviour.

The total energy consumption of a dwelling is that required to support all energy consuming end-uses, inclusive of the losses due to appliance and system efficiencies. The end-uses may have complex inter-related effects with regards to energy consumption. For example, the energy consumption of most common appliances results in heating of the conditioned living area. The energy consumption can be supplied by one or more secondary energy sources and includes on-site generation and passive solar gains. The sum of each dwelling's energy consumption for a given area (e.g. city and country) results in a regional or national residential sector energy consumption, the modeling of which is the topic of interest for this review.

Energy consumption modeling of buildings seeks to quantify energy requirements as a function of input parameters. Models may be used for a variety of reasons, the most common being the determination of regional or national energy supply requirements (macro-scale) and the change in energy consumption of a particular dwelling due to an upgrade or addition of technology (micro-scale). Modeling of this nature is useful as it can guide decisions of policy regarding the residential stock, both old and new. By quantifying the consumption and predicting the impact or savings due to retrofits and new materials and technology, decisions can be made to support energy supply, retrofit and technology incentives, new building code, or even demolition and re-construction.

Residential energy models may focus on a thermal zone, building, neighbourhood, city, state or province, region, or nation. The level of detail of input parameters is a function of data availability, model focus and purpose, and assumptions. Increased detail allows for a more comprehensive investigation of particulars, although accurate assumptions may significantly ease the modeling process and provide suitable results.

Emphasis of this review is placed on models that are or could be used to model the residential sector energy consumption. Energy consumption models of this scope involve an approximation of the residential stock and a methodology for estimating the energy consumption of the stock. Such models are useful to formulate policy decisions regarding the residential stock, both old and new. By quantifying the consumption and predicting the impact or savings due to construction/demolition, retrofits and new materials and technology, decisions can be made to support energy supply, retrofit and technology incentives, new building codes, or even demolition and re-construction. This review of residential sector energy consumption models introduces the modeling techniques, reviews the published literature and concludes with an analysis of the strengths and weaknesses of the techniques.

2. Objective

The objective of this paper is to provide an up-to-date review of the various modeling techniques used for modeling residential sector energy consumption. Two distinct approaches are identified: top-down and bottom-up. Each technique relies on different levels of input information, different calculation or simulation techniques, and provides results with different applicability. A critical review of each technique, focusing on the strengths, shortcomings and purposes, is provided along with a review of models reported in the literature.

3. Modeling methodologies

Residential energy models rely on input data from which to calculate or simulate energy consumption. The level of detail of the available input data can vary dramatically, resulting in the use of different modeling techniques which seek to take advantage of the available information. These different modeling techniques have different strengths, weaknesses, capability, and applicability.

3.1. Types and sources of information

Depending on the modeling methodology to be used, the input data required to develop residential energy models includes information on the physical characteristics of the dwellings, occupants and their appliances, historical energy consumption, climatic conditions, and macroeconomic indicators. The information can be collected independently or concurrently, can be national aggregate or individual dwelling values, and vary greatly in level of detail. The basic information collection method is by survey, the results of which are published in raw or analyzed form.

The preliminary estimate of the total residential sector energy consumption is usually published by governments which compile gross energy values submitted by energy providers (examples are Canada [3], USA [4], UK [5], and China [6]). These estimates provide indicators as to sector energy consumption but may be inaccurate as they do not account for unreported energy or on-site generation. A more detailed source of energy consumption data, typically on a monthly basis and for each dwelling, is the billing records of energy suppliers (e.g. monthly dwelling electricity bill). However, with no additional housing information these energy consumption values are difficult to correlate due to the wide variety of dwellings and occupants.

To provide more detailed information than the above aggregate values, housing surveys are conducted. These surveys target a sample of the population to determine building and occupant characteristics and appliance penetration levels (examples are Canada [7], USA [8], and UK [9]). The Tyndall Centre conducted a worldwide review of such surveys [10]. Surveys typically attempt to define the house geometry and thermal envelope, ownership of appliances, occupants and their use of appliances and preferred settings, and demographic characteristics. In addition, surveys may attempt to obtain the energy suppliers' billing data (described above) and alternative energy source information (e.g. unreported wood usage) to correlate the energy consumption of the house with its characteristics identified during the survey. This allows for calibration through reconciliation of a model's predicted energy consumption with actual energy billing data. This level of information is superior to the previously mentioned energy supplier values; however, it is limited due to collection difficulties and cost, and therefore it is imperative that the selected sample be highly representative of the population. Also, occupant descriptions of their appliance use are highly subjective and can be influenced by the season during which the survey takes place [7]. Examples of surveys which have been condensed for the purpose of energy simulation are [11,12].

Elimination of subjective appliance usage estimation is achieved by "sub-metering". This method places energy metering devices on the large energy consuming appliances within the

household to determine both their component of the house energy consumption and their usage profile as a function of time (e.g. [13]). This level of information is rare due to its prohibitive cost.

Estimated total sector energy, individual billing data, surveys, and sub-metering have been used to varying degrees in the development of residential energy consumption models. The determination of which information is used depends on availability and model's purpose. The purpose of models ranges widely and may be directed towards determining supply requirements, price and income elasticity, and the energy consumption impacts of upgrades, technologies, or changes to behavioural patterns.

3.2. Techniques to model energy consumption

Techniques used to model residential energy consumption can broadly be grouped into two categories, "top-down" and "bottom-up". The terminology is with reference to the hierarchal position of data inputs as compared to the housing sector as a whole. Top-down models utilize the estimate of total residential sector energy consumption and other pertinent variables to *attribute* the energy consumption to characteristics of the entire housing sector. In contrast, bottom-up models *calculate* the energy consumption of individual or groups of houses and then extrapolate these results to represent the region or nation.

Groupings of top-down and bottom-up techniques for modeling residential energy consumption are shown in Fig. 2 and are discussed in the following sections.

3.2.1. Overview of the top-down approach

The top-down approach treats the residential sector as an energy sink and does not distinguish energy consumption due to individual end-uses. Top-down models determine the effect on energy consumption due to ongoing long-term changes or transitions within the residential sector, primarily for the purpose of determining supply requirements. Variables which are commonly used by top-down models include macroeconomic indicators (gross domestic product (GDP), employment rates, and price indices), climatic conditions, housing construction/demolition rates, and estimates of appliance ownership and number of units in the residential sector.

Fig. 2 shows two groups of top-down models: *econometric* and *technological*. Econometric models are based primarily on price (of, for example, energy and appliances) and income. Technological models attribute the energy consumption to broad characteristics of the entire housing stock such as appliance ownership trends. In addition there are models which utilize techniques from both groups.

Top-down models operate on an equilibrium framework which balances the historical energy consumption with that estimated based on input variables. The strengths of top-down modeling are the need for only aggregate data which are widely available, simplicity, and reliance on historic residential sector energy values which provide "inertia" to the model. As the housing sector rarely undergoes paradigm shifts (e.g. electrification and energy shocks), a weighted model provides good prediction capability for small deviations from the status quo. For example, if housing construction increased the number of units by 2%, an increase in total residential energy consumption of 1.5% might be estimated by the top-down model, as new houses are likely more energy efficient. If this construction was increased to 10% of the units the top-down model could have difficulty in producing an appropriate estimate as the vintage distribution of the housing stock would have changed significantly.

The reliance on historical data is also a drawback as top-down models have no inherent capability to model discontinuous advances in technology. Furthermore, the lack of detail regarding the energy consumption of individual end-uses eliminates the capability of identifying key areas for improvements for the reduction of energy consumption.

3.2.2. Overview of the bottom-up approach

The bottom-up approach encompasses all models which use input data from a hierarchal level less than that of the sector as a whole. Models can account for the energy consumption of individual end-uses, individual houses, or groups of houses and are then extrapolated to represent the region or nation based on the representative weight of the modeled sample. The variety of data inputs results in the groups and sub-groups of the bottom-up approach as shown in Fig. 2.

Statistical methods (SM) rely on historical information and types of regression analysis which are used to attribute dwelling energy consumption to particular end-uses. Once the relationships between end-uses and energy consumption have been established, the model can be used to estimate the energy consumption of dwellings representative of the residential stock. *Engineering* methods (EM) explicitly account for the energy consumption of end-uses based on power ratings and use of equipment and systems and/or heat transfer and thermodynamic relationships.

Common input data to bottom-up models include dwelling properties such as geometry, envelope fabric, equipment and appliances, climate properties, as well as indoor temperatures, occupancy schedules and equipment use. This high level of detail is a strength of bottom-up modeling and gives it the ability to model technological options. Bottom-up models have the capability of determining the energy consumption of each end-use and in doing so can identify areas for improvement. As energy consumption is calculated, the bottom-up approach has the capability of determining the total energy consumption of the residential

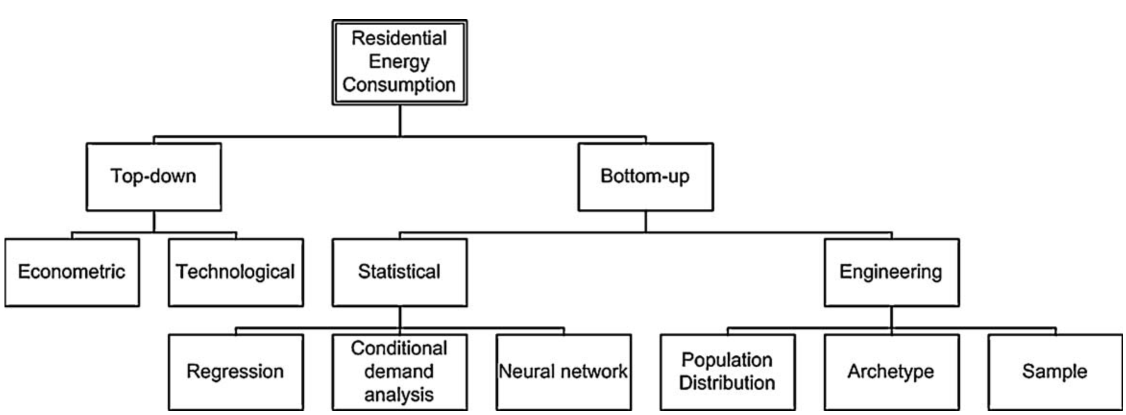

Fig. 2. Top-down and bottom-up modeling techniques for estimating the regional or national residential energy consumption.

sector without relying on historical data. The primary drawback caused by this level of detail is that the input data requirement is greater than that of top-down models and the calculation or simulation techniques of the bottom-up models can be complex.

In all cases the bottom-up models must be extrapolated to represent the housing sector. This is accomplished using a weighting for each modeled house or group of houses based on its representation of the sector.

A notable capability of the bottom-up approach is its ability to explicitly address the effect of occupant behaviour and "free energy" gains such as passive solar gains. Although free energy gains have historically been neglected during residential analysis, they are now a common design point as focus is placed on alternative energy technologies. Statistical methods attribute all of the *measured* energy consumption to end-uses and in doing so incorporate the occupant's behaviour with regards to use and settings of appliances. However, if all energy sources are not accounted for, the end-use energy consumption estimates are derated by this consumption difference. Based in its physical principle roots, the EM has the ability to capture the additional energy consumption level based on requirements, inclusive of free energy. However, occupant behaviour must be estimated which is difficult as behaviour has been shown to vary widely and in unpredictable ways.

The following sections examine the modeling techniques by reviewing published models. The applicability, basic methodology and major conclusions found by the researchers are listed. There is a tendency towards chronological order to facilitate understanding of the modeling technique development stream and contributions by the authors. Certain techniques were found to follow a clear development stream (e.g. conditional demand analysis) while others contain a wide variety of techniques and are discontinuous. Emphasis is placed on modeling technique development and less on the simple application to a new region.

4. Top-down models

The use and development of the top-down modeling approach proliferated with the energy crisis of the late 1970s. In an effort to understand consumer behaviour with changing supply and pricing, broad econometric models were developed for national energy planning. These models require little detail of the actual consumption processes. The models treat the residential sector as an energy sink and regress or apply factors that affect consumption to determine trends. Most top-down models rely on similar statistical data and economic theory.

As the housing stock in most regions is continuously undergoing improvement and increase, simply modeling the energy consumption solely as a function of economic variables is short-termed. Hirst et al. [14] initiated an annual housing energy model of the USA. Their model relied on econometric variables and included a component for growth/contraction of the housing stock. Their work was expanded and improved over the following years resulting in an econometric model which had both housing and technology components [15,16]. The housing component evaluates the number of houses based on census data, housing attrition and new construction. The technology component increases or decreases the energy intensiveness of the appliances as a function of capital cost. The economic component evaluates changes in consumption based on expected behavioural changes and efficiency upgrades made to the technology component. Finally, market penetration is considered a function of income and demand/supply. The simulation model combines the changes in outputs of the components and estimates the energy consumption given historic energy consumption values. The authors felt their model was sensitive to major demographic, economic and technological factors, but recognized the need to continually update all assumed information to improve quality.

Saha and Stephenson [17] developed a similar model for New Zealand although it had a technological focus. Their economic and housing components drive separate analysis of SH, DHW, and cooking, and are added to obtain total consumption. Their basic energy balance, as shown in Eq. (1), determines the annual energy consumption of each fuel used to support each end-use group as a function of stock, ownership, appliance ratings and use. Using historical data, their prediction capability was excellent throughout the 1960s and 1970s although there is significant divergence toward the latter half of the 1970s. This may be due to the model not accounting for shifts in home insulation levels

$$E_{\mathrm{an},e,f} = S \cdot C_{e,f} \cdot R_{e,f} \cdot U_{e,f} \tag{1}$$

where E is the annual energy consumption of end-use group e, corresponding to fuel type, f, S is the level of applicable housing stock, C is the appliance ownership level, R is the rating of all appliances within an end-use group, and U is a use factor.

Haas and Schipper [18] recognized that energy consumption of the housing stock is poorly modeled by only a few econometric indicators. They identified "irreversible improvements in technical efficiency" which are a result of consumer response that not only reduces energy consumption due to rising price, but responds by making upgrades to their dwelling. Consequently a subsequent reduction in price would not cause a perfectly elastic rebound. To quantify this asymmetrical elasticity, they developed econometric models for the USA, Japan, Sweden, West Germany and the UK based on the time periods of: 1970–1993, 1970–1982, and 1982–1983. They found very flat (nearly zero) rebound of energy consumption after periods of increased price, suggesting the typical price elasticity is a diluted average. They also state saturation of appliances can lead to reduced income elasticity and they found limited correlation between increasing technological efficiency leading to increased energy use. When the authors included technological energy intensity in their model (using a bottom up approach based on individual appliance ratings) they found reduced error and that the irreversible share of price elasticity became hidden in the coefficient of intensity.

Two tier econometric models that evaluate choice of system (discrete) and utilization (continuous) are common. Nesbakken [19] developed such a model for Norway, testing sensitivity and stability across a range of income and pricing. The author considered three years of expenditure surveys and energy consumption to determine differences along the time dimension. Their findings were consistent with negative price elasticity and maximization of utility. Different income groups resulted in similar findings although the responses were slightly higher for higher income groups.

Bentzen and Engsted [20] revived simple economic modeling of residential energy consumption. They tested the following three annual energy consumption regression models for Denmark:

$$E_{\mathrm{an},t} = b + c_1 E_{\mathrm{an},t-1} + c_2 I_{\mathrm{disp},t} + c_3 Pc_t \tag{2}$$

$$E_{\mathrm{an},t} = b + c_1 E_{\mathrm{an},t-1} + c_2 I_{\mathrm{disp},t} + c_3 Pc_t + c_4 HDD_t \tag{3}$$

$$E_{\mathrm{an},t} = b + c_1 E_{\mathrm{an},t-1} + c_2 I_{\mathrm{disp},t} + c_3 Pc_t + c_4 HDD_t + c_5 Pc_{t-1} \tag{4}$$

where E is the annual energy consumption for year, t, I is the disposable household income, Pc is the price of energy, HDD is the heating degree days, b is a constant, and c are coefficients.

From 36 years of data they found that, in all three cases, long-term energy consumption was strongly affected by income and lagged energy consumption, and lagged pricing trumped current

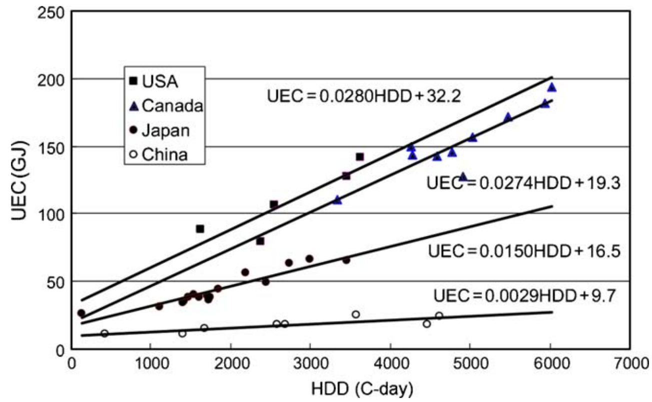

Fig. 3. Comparison of National UEC values [21].

pricing. Their findings indicate that future energy price must increase with income to maintain the current consumption level.

Using aggregate national residential energy values, Zhang [21] compared international values of unit energy consumption (UEC) to determine to potential changes in the sector's energy consumption. The author calculated the UEC for various regions of China based on energy consumption and the number of residences, and compared the Chinese UEC with those of other countries. The results indicate that when normalized for heating requirements based on climate (i.e. heating degree days (HDD)), Japan uses approximately half the UEC of the USA and Canada, as shown in Fig. 3. This may be attributed in part to the high ratio of apartment buildings in Japan (40%). China is closer to one quarter of the North American UEC, owing to limited adoption of space heating devices. The paper also discusses the potential of the Chinese residential sector following the North American or Japanese energy consumption characteristics. Interestingly, the model identified that although China is growing, the secondary energy consumption of the residential sector has remained constant due to switching away from coal as a fuel.

Ozturk et al. [22] and Canyurt et al. [23] proposed the use of genetic algorithms (GA) to determine the relationships between Turkish residential–commercial energy consumption and the following: GDP, population, import/export, house production, cement production and appliance sales. GA models utilize concepts of biology and Darwin's theory of survival of the fittest. Initiated chromosomes (potential solutions) are assessed on the basis of fit (sum of squared errors) to determine their level of participation. Chromosomes are crossed to exchange potential solution characteristics (coefficients of input variables) with the potential of mutations to account for solutions which were not part of the initial population. The authors' GA model estimates the coefficients of the linear model based on the aforementioned variables and their combinations. The resultant model had excellent fit with the calibration information and their projections through the year 2020 were similar to other models. They note the benefits of the GA as requiring limited information and easy development.

The national energy modeling system (NEMS) incorporates a current econometric energy model of the USA housing stock [24]. The model is used for mid-term forecasting and policy analysis. It includes five components: housing stock forecast, technology, appliance stock forecast, building shell integrity, and distributed generation equipment. The appliance stock component places emphasis on appliance lifetime and saturation levels, functions which have been studied in depth for Canada by Young [25]. The distributed generation component indicates that emphasis is being placed on the integration of non-traditional energy sources; it looks at system cost, efficiency, penetration parameters, and solar insolation levels. The calculated energy consumption is then fed back into the NEMS for use with other models and overall energy supply prediction.

Using the entire building register of Goteborg (68,200 buildings) and energy data from the largest energy supplier, Tornber and Thuvander [26] developed an energy model of the building stock. The energy data was measured at metering stations, and was distributed among connected buildings on the basis of building use and age. The model utilizes geographical information systems (GIS) to visually assist the assessment of the consumption rates of different energy sources throughout Goteborg. Although they were unable to directly link the energy consumption to individual buildings, their spatial model clearly identifies energy use within groups of buildings and may be used for identification of high consumption areas.

Labandeira et al. [27] extended a regression model by developing a six equation demand model of Spanish residential energy consumption. Separate equations were developed for energy consumption associated with: electricity, natural gas, propane, automotive fuel, public transport, and food. They found that these products are price inelastic. They regressed the energy consumption of over 27,000 houses as a function of demographic, macroeconomic, and climate variables. They experienced reduced multicollinearity problems as their dataset covered an extended period of time (changing appliances ownership) and this also provided longer-term elasticity assessment.

Siller et al. [28] created a model of the Swiss residential sector to test the impacts of renovations and new construction in an attempt to achieve energy consumption and greenhouse gas emissions targets. Their model is based on the effective reference area which is a measure of the effective heated area and is calculated based on census data. They developed modeling matrices which account for the renovation of buildings and if demand is met, new construction of buildings. In calculating energy consumption they use building type, energy standards, efficiency, and heat demand per area. The update of the housing stock is through new construction and renovation, of which the latter is only occasionally realized. They point out that these estimates have a strong affect on model uncertainty.

Balaras et al. [29] constructed a renovation model of the Hellenic housing stock. Using an assessment of the housing stock and current energy consumption figures, they estimated the impact of fourteen different energy conservation measures that were applied to houses in need of refurbishment. They found the housing stock lacking in insulation and predicted that adding insulation to the stock would save 49% of current space heating energy consumption.

5. Bottom-up models

The bottom-up approach was developed to identify the contribution of each end-use towards the aggregate energy consumption value of the residential stock. This refines the understanding of the details associated with the energy consumption.

There are two distinct categories used in the bottom-up approach to evaluate the energy consumption of particular end-uses. The SM utilizes dwelling energy consumption values from a sample of houses and one of a variety of *techniques* to regress the relationships between the end-uses and the energy consumption. SM models can utilize macroeconomic, energy price and income, and other regional or national indicators, thereby gaining the strengths of the top-down approach. The EM relies on information of the dwelling characteristics and end-uses themselves to calculate the energy consumption based on power ratings and use characteristics and/or heat transfer and thermodynamic principles. Consequently, the engineering technique has strengths

such as the ability to model new technologies based solely on their traits. Once developed, the bottom-up models may be used to estimate the energy consumption of houses representative of the residential stock and then these results can be extrapolated to be representative of the regional or national residential sector.

5.1. Statistical techniques

The vast quantity of customer energy billing information stored at the major energy suppliers worldwide is an unprecedented data source for energy modeling. Researchers have applied a variety of SM techniques to utilize this and other information to regress the energy consumption as a function of house characteristics. A capability of the SM techniques is their ability to discern the effect of occupant behaviour. This is of benefit to residential modeling as occupant behaviour has been found to range widely and is poorly represented by simplified estimates [2,30,31].

The three well-documented techniques, all of which use a sample of houses, are:

- Regression—The regression technique uses regression analysis to determine the coefficients of the model corresponding to the input parameters. These models regress the aggregate dwelling energy consumption onto parameters or combinations of parameters which are expected to affect energy consumption. The model is evaluated based on goodness of fit. Input variables which are determined to have a negligible effect are removed for simplicity. Based on the combinations of inputs, the model's coefficients may or may not have physical significance.
- Conditional demand analysis (CDA)—The CDA method performs regression based on the presence of end-use appliances. By regressing total dwelling energy consumption onto the list of owned appliances which are indicated as a binary or count variable, the determined coefficients represent the use level and rating. The primary strength of this technique is the ease of obtaining the required input information: a simple appliance survey from the occupant and energy billing data from the energy supplier. However, it does require a dataset with a variety of appliance ownership throughout the sample. This technique exploits the differences in ownership to determine each appliance's component of the total dwelling energy consumption. In order for the CDA technique to produce reliable results, and depending on the number of variables used, data from hundreds or even thousands of dwellings are required.
- Neural network (NN)—The NN technique utilizes a simplified mathematical model based on the densely interconnected parallel structure of biological neural networks. The technique allows all end-uses to affect one another through a series of parallel "neurons". Each neuron has a bias term and array of coefficients that are multiplied by the value of the preceding layer's neurons. Similar to regression models it seeks to minimize error and may apply scaling and activation functions to account for non-linearity. As it is a parallel model, the coefficients have no physical significance.

5.1.1. Regression

In an effort to identify unusual metering occurrences (e.g. broken meter) and evaluate the level of households with more than one energy source for space heating, Hirst et al. [32] used the Princeton scorekeeping model with monthly or bimonthly energy supplier billing data. They examined the weather and non-weather sensitive elements of the household energy consumption of dwellings by regressing the energy billing data onto a non-weather dependent constant and a weather dependent coefficient based on HDD, as shown in Eq. (5). They left the reference temperature for determination of the HDD as a variable, to be adjusted between 4 °C and 24 °C in an effort to reduce error and increase the multiple correlation coefficient (R^2). The adjustment of T_{ref} was shown to be effective by Jones and Harp [33] who reduced it from the accepted value of 18.0–16.9 °C and achieved more representative results for the space heating requirements of Oklahoma

$$E_{\mathrm{an},t} = b + c\ \mathrm{HDD}_t(T_{\mathrm{ref}}) \tag{5}$$

where E is the annual energy billing data from period, t, HDD is the heating degree days with reference temperature, T_{ref}, b is constant, and c is a coefficient.

The coefficients in the above model were termed "fingerprints" and directed towards determining unusual metering occurrences and identifying the use of alternative space heating fuels when comparing the monthly measured house energy consumption to that predicted by the model. Recently, a similar analysis was conducted by Raffio et al. [34] with the goal of identifying energy conservation potential within a regional area. A similar model with "energy signature" coefficients was developed. These coefficients were compared regionally and also evaluated over the course of the seasons for the identification of patterns which can be used to assess potential energy conserving changes. The authors give examples such as the application of DHW conserving devices to dwellings with high non-weather dependent energy consumption and the application of programmable thermostats to high balance point T_{ref} buildings. While the model cannot determine the impact of these changes, it may identify the potential for application. The primary advantages of this model are simplicity, only requiring billing data, and the capability of normalized comparison across many different residences using a sliding scale which is continuously updated from new billing data. Utilizing larger sets of billing data, the models can become descriptive of a nation.

Tonn and White [35] developed a regression model with four simultaneous equations: separate equations of electricity use associated with SH and AL, wood use, and indoor temperature. Data was sourced from 100 sub-metered homes that utilized wood heat. In an attempt to encompass occupant behaviour they conducted an extensive survey (300 questions) which asked questions related to goals and motivations, and occupants self-defined socioeconomic response. Their desire was to determine the motivation or ethical considerations in energy use. They developed 30 different regression models, consecutively eliminating variables with insignificant impact. Their four regression equations achieved R^2 values ranging from 0.80 to 0.91. While housing characteristics played a distinct role in the models, they found ethical motivations outweigh economic motivations. They found education level and age of the head of household not to affect any of the four equations.Douthitt [36] constructed a model of residential space heating fuel use in Canada by regressing consumption as a function of present and historic fuel price, substitute fuel price, total fuel consumption, and a vector of building structure, climatic, and occupant characteristics. Using 370 records, they achieved R^2 values equal to 0.52 (natural gas), 0.76 (heating oil), 0.37 (electricity with natural gas available), and 0.79 (electricity with no natural gas available). The author found that the sample with energy source alternatives achieve near unity price elasticity, the implication being towards fuel subsidies being ineffective at reducing annual fuel cost per house. Income elasticity was also very unitary, indicating that providing subsidies (in effect income) to low-income families would result in increased usage.

Fung et al. [37] adopted the regression techniques of [36] and others to determine the impact on Canadian residential energy consumption due to energy price, demographics, and weather and equipment characteristics. They found both short and long term fuel price elasticity to be negative, although the long term was

larger in magnitude. Income elasticity was found to be insignificant. These results were similar for each end-use group (i.e. SH/SC, DHW, and AL).

5.1.2. Conditional demand analysis

Parti and Parti [38] developed the CDA method given the availability of a detailed survey of appliance and occupants of over 5000 households and their corresponding monthly electrical billing data from the electricity utility in San Diego. They recognized the limitations inherent to an engineering model that approximates occupant behaviour based on theoretical considerations and therefore they attempted to determine the use level of individual appliance based on regression methods. They proposed a *conditional demand regression equation* based on the indication of appliance ownership and expected relations with other house characteristics such as floor area or demographic factors gathered from a survey.

Their regression equation, one for each month of a year of billing data, take the form

$$E_{\text{mo}} = \sum_{i} \sum_{app} c_{app,i}(V_i C_{app}) \qquad (6)$$

where E is the monthly electrical energy consumption, C is a variable indicating appliance presence or count for appliances, *app*, V is a set of interaction variables with elements, i, such as the number of occupants, income, and floor area, and c is a coefficient.

The appliance at $app = 0$ is unspecified to account for appliances whose presence were not explicitly surveyed and the interaction variable when $i = 0$ accounts for appliance energy consumption unrelated to interactions with other surveyed information.

The authors specified conditions to limit use of the significant appliances to help in regression coefficient determination. These included disallowing air conditioning from November through March and space heating from July through August. They considered the dominant electrical end-uses: air conditioning, space heating, water heating, and common appliances which include dishwasher, cooking range, dryer, and refrigerators and freezers. The interaction variables corresponding to end-use groups are shown in Table 1.

The final model coefficients were indicative of appliance use and resulted in R^2 values ranging from 0.58 to 0.65. As the regression model included demographic variables, the authors were able to determine econometric effects such as income and energy price elasticity. In comparison with engineering estimates, their CDA model under predicts energy consumption of space heating and over predicts energy consumption of water heating and common appliances. The authors believe they could incorporate solar technologies, but recognize the need for sufficient samples and associated annual dwelling energy consumption data. They see the benefits of the CDA method including the disaggregation of energy consumption by end-use without sub-metering and the inclusion of behavioural aspects within the coefficients.

Using 15 min interval load data from 100 Los Angeles electricity customers, Aigner et al. [39] utilized the CDA method to determine hourly regression equations. Based on constant appliance dummy variables, they found the regression resulted in inadequate coefficients. For example, the magnitude of coefficients (indicating use level) changed throughout the day with load level, but the relationship between different appliances did not, indicating that the coefficients represent an average use level and are not indicative of the daily use profile. To promote differences in the coefficients, the authors imposed restrictive windows of appliance use; specifically, laundry and cooking devices were excluded over the period of 2–5AM. Their results compared to actual occupant load profiles better than conventional CDA.

Caves et al. [40] developed a CDA model of the residential electricity energy consumption of Los Angeles customers by incorporating prior information through the use of Bayesian inference in an effort to reduce unreasonable or negative coefficients estimated by the conventional CDA method. The prior information was developed by using the EM to model appliances and systems and estimate load profiles. These profiles were used to calculate coefficients of use, similar to the CDA coefficients. A typical CDA model, based on a sample of 129 houses with daily energy consumption information (excluding weekends) for the summertime in Los Angeles was constructed using a method similar to [38]. Given the confidence levels of the EM coefficients and the CDA method coefficients, these weighted values are combined using Bayesian techniques to estimate final coefficients of the CDA regression model. This combination approach reduces the multicollinearity effects which can result in negative or unreasonable coefficients; however, it relies on engineering estimates of occupant behaviour.

Bartels and Fiebig propose an alternative method that incorporates sub-metered end-use energy consumption of a subset of the sample into the CDA model [41,42]. This was accomplished by removing the energy consumption and independent variables of the measured appliances within the sub-metered subset of houses. In doing this, they reduced the regression requirements of the subset and weighted the regression of the coefficients of the remaining sample. One advantage of this method is that the elimination of certain end-use consumption of the sub-metered subset increases the resolution and therefore the confidence level of the estimates of non-metered appliances. This is an improvement over using the EM to determine estimates of certain end-uses based on occupant behaviour.

LaFrance and Perron [43] furthered the CDA method by incorporating energy consumption data from three different years over a decade for Quebec. This allowed for the determination of changes in annual energy consumption as a function of changing appliance stock (specifically the addition of electric space heat), and long term pricing response. The database they used was significantly larger than previous efforts, approximately 100,000 samples in total, and contained additional information such as weather relations (heating and cooling degree days), cords of wood (an important energy source for space heating in Quebec), water heater characteristics and certain demographics. These qualities increased the R^2 coefficient to a range of 0.55–0.70.

Their CDA model for each year of available data allowed them to identify changing ownership which evolved to larger, more

Table 1
Interaction variables which have an effect on the energy consumption of particular appliances or equipment [38].

Appliances and equipment	Interaction variables				
	Number of occupants	Electricity price	Household income	Floor area	Heating/cooling per unit area
Common appliances	✓	✓	✓		
Refrigerator	✓				
Hot water	✓	✓	✓		
Space heating and cooling		✓	✓	✓	✓

consuming appliances throughout the period. Strong relationships were identified between incentive activities and appliance penetration. They found the CDA method could estimate the space heating energy consumption associated with wood as an energy source better than engineering estimates. This is due to direct occupant control over wood burning devices (e.g. damper control) and also the wide range of efficiency during operation. The authors identify a multicollinearity issue, the inability to determine which of two or more near linear related independent variables are having an impact on the dependent variable (energy consumption). They found that the nearly ubiquitous presence of the refrigerator and small unspecified appliances made it difficult to determine their impacts. They suggest improving the estimation by further distinguishing certain appliances by their characteristics (e.g. age, size, and number of doors of a refrigerator). Furthermore, they identify that the net energy consumption of the households, as determined by billing data, is not inclusive of passive energy gains and therefore is not representative of the actual consumption of the house, only the net measured consumption. However, this does not impede the relative comparison of two appliances as the passive gains remain identical.

Hsiao et al. [44] combined the work of [40] and [41] by utilizing sub-metered end-use energy consumption as the Bayesian inference prior information. The approach used a small set (49 households) of direct metered end-use data and a larger set which included billing and survey information from Ontario Hydro customers (347 households). The prior information is formed from the mean and variance of the end-use data, thereby providing values which incorporate behavioural aspects better than simple EM estimation.

Bartels and Fiebig [45] further improved upon this modeling technique development stream by increasing "efficiency" of sub-metering by conducting a review of the house appliance survey prior to the sub-metering measurement. They identified houses which would contribute the most to the model by being sub-metered. Based on a preliminary review of 1901 house appliance surveys the authors chose 250 appropriate houses and certain appliances to sub-meter. Sub-metering was also focused on freezers and lighting, areas which posed significant difficulty due to multicollinearity in all previous CDA efforts. Given excellent sub-metered data they attempted to extend their annual model to a half-hour model (48 CDA equations per day); however this resulted in a drop in the R^2 values from 0.66 to 0.34.

Lins et al. [46] developed a national CDA model for Brazil featuring 10,818 dwellings based on monthly energy consumption. As the model covered a wide north-south geographical area with varying climatic conditions, they found it difficult to obtain R^2 greater than 0.5.

Aydinalp-Koksal and Ugursal [47] constructed a national residential CDA model based on over 8000 records from a 1993 Canadian national residential energy consumption survey [48]. To be applicable to the entire energy consumption of the Canadian residential sector, the authors developed three CDA models corresponding to the dominant energy sources in Canada: electricity, natural gas, and oil. As the survey data was highly detailed, new descriptive variables were added to the CDA equations including: programmable thermostats, heat recovery ventilation, heating equipment efficiency, windows and doors, aerators and laundry loads. They mention that the number of independent variables should be limited to facilitate regression and reduce poor approximations of smaller appliances which may be indistinguishable.

The three CDA models achieved R^2 values ranging from 0.79 to 0.89 which may be a result of their annual model that averages the daily and seasonal effects. Certain end-uses were under or overestimated similar to [38]. The authors examined socio-economic effects using the model. The effects were linear, which caused concern as the model was driven to extremity values such as one occupant. Interestingly, the presence of children and adults equivalently affected the electricity consumption of common appliances, lighting, and space cooling. The CDA models were compared to detailed NN and EM models conducted on the same database. The CDA method always under predicted the NN model, and under predicted the EM in the AL, cooling, and SH categories, but not the DHW category. The authors note that the CDA model coefficients are more transparent and their implications better understood in comparison with the NN method.

5.1.3. Neural network

The use of NN methods in modeling residential energy consumption has historically been limited, possibly due to the computational and data requirements or the lack of physical significance of the coefficients relating dwelling characteristics to total energy consumption. Because of their ability to capture non-linear characteristics, NN models have been used to forecast the varying electrical loads seen by utilities. Aydinalp et al. [49] provides a review of the literature and discusses the development of NN models for electrical load forecasting purposes, stating that hundreds of models have been developed. They further report that modeling of energy consumption of individual buildings using NN originated and evolved throughout the 1990s beginning with commercial buildings and progressing in complexity. Specifically noted is an hourly building energy simulation contest reported by Kreider and Haberl [50] in which the top contenders used "connectionist" methods (e.g. NN).

A simplified NN is shown in Fig. 4. Interconnectivity between each characteristic is found at hidden neurons. Coefficients for each input to a hidden or output neuron are included in respective vectors "$\bar{V}$". The neurons are also biased by the term "b". For a particular NN arrangement (3:2:1 shown in the figure) and appropriate scaling and activation functions, the coefficient vector and bias are adjusted using a variety of techniques to minimize error of the model. Once the values are determined, the model can be used calculate the energy consumption as a function of different inputs.

Issa et al. [51] introduced the application of NN modeling to the residential energy consumption of a region. They described the development of a NN model that uses energy performance index (EPI) and conditioned floor areas of a group of dwellings with billing data. The EPI is an assigned energy efficiency rating based on housing components. Their NN model bridged the gap between actual energy consumption and the EPI rating. No results were declared.

Mihalakakou et al. [52] created an energy model of a house in Greece using the NN methodology based on atmospheric conditions. Inputs included air temperature and solar radiation and the NN was trained using five years of hourly energy consumption

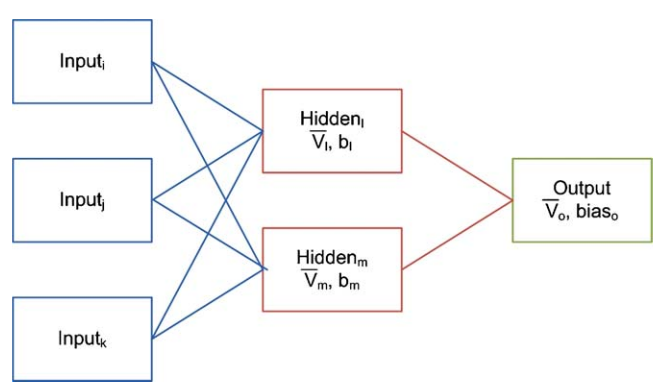

Fig. 4. Simplified NN with three inputs, two hidden neurons with coefficient arrays "$\bar{V}$" and bias "b", and one output.

data. Results of predicted energy consumption for the dwelling were excellent on an hourly basis. This can be attributed to the unprecedented amount of hourly "training" data used to calibrate the model. Sadly, while multiyear data was available, dates were not indicated as an input to the NN and therefore annual changes were not accounted for. This method may be extrapolated on a monthly basis using energy supplier billing data to a region of houses. It would therefore become a tool to estimate the variation in energy consumption between cold or warm years.

Aydinalp et al. [49,53] introduced a comprehensive national residential energy consumption model using the NN methodology. They divided it into three separate models: appliances, lighting and cooling (ALC); DHW; and SH. To differentiate the electrical energy consumption for ALC from DHW and SH, only houses which used natural gas or oil for heating loads were used to train the ALC model. The NN models used the 1993 Canadian national residential energy consumption survey [48].

The ALC NN model utilized appliance and heating system information, as well as demographic information for a total of 55 inputs. They trained the model using the annual ALC electricity consumption billing data and inputs from a 741 household "training dataset". The network was optimized by varying properties such as learning algorithm, scaling interval, and hidden layers, which were evaluated by maximizing the R^2 values. Once the network properties were determined it took 182 training cycles to achieve the final nodal coefficients and bias values.

A "testing set" of 247 houses was used to compare the ALC NN model with the EM. Prediction capabilities of the NN surpassed that of the EM, with R^2 values of 0.91 and 0.78, respectively when compared to the metered energy consumption. The authors commented on the ability of the NN to determine an individual appliance's component of the aggregate energy consumption by simply removing its presence from the modeled house. Appliance values compared well with other studies, but were not compared to sub-metered data. Specifically, the refrigerator consumption was not found to be rational, indicating an appliance saturation issue similar to that of the CDA method. As demographic factors were included as inputs, socioeconomic response was analyzed. It was found that ALC energy consumption increased as a second order polynomial as a function of household income.

Aydinalp et al. [54] extended the NN methodology from ALC loads of the Canadian residential sector to loads due to SH and DHW. This was accomplished using similar methods to those described above, using the remaining dataset that contained alternative energy sources. The ALC NN was also used to remove the ALC component when solving for SH and DHW provided by electricity sources. Values of R^2 were again higher than corresponding EM models based on the same data; however, Fig. 5 shows the SH energy consumption predicted by the NN has a biased error. A socioeconomic analysis was conducted and both SH and DHW energy consumption were found to vary linearly with income.

Yang et al. [55] presented a technique for an "adaptive" NN which functions by accumulating additional energy data or using a sliding window of recent energy data. This extends upon the static predictions made by conventional NN, and allows for the coefficients and bias to be updated as new information becomes available. They found that given a previously trained network, the updating of the coefficient and bias values to represent new data takes less time as the initial values are close to the final state. This technique could be applied for continuous update, similar to that of the top-down technique used by the USA EIA [24].

5.2. Engineering method

The EM accounts for energy consumption of the end-uses based on their ratings or characteristics. The EM is the only method that

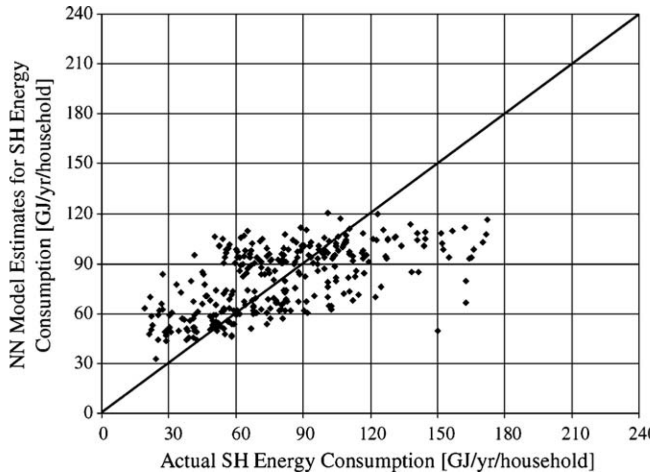

Fig. 5. Comparison of SH energy consumption using the NN technique to actual SH energy consumption [54].

can fully develop the energy consumption of the sector without any historical energy consumption information. Models can be as simple as an estimate of SH based on the climate through the use of HDD or as detailed as a complete thermodynamic and heat transfer analysis on all end-uses within the dwelling. As it functions based on the physics of the end-uses, the EM has the highest degree of flexibility and capability with regard to modeling new technologies which have no historical consumption data. However, occupant behaviour must be assumed. As occupant behaviour varies widely, this is difficult to estimate. Three EM techniques are identified in this review:

- Distributions—This technique utilizes distributions of appliance ownership and use with common appliance ratings to calculate the energy consumption of each end-use. As end-uses are typically calculated separately, this technique does not account for interactions amongst end-uses. The product of appliance ownership, appliance use, appliance rating and the inverse of appliance efficiency results in the energy consumption. By aggregating the appliance consumptions on a regional or national scale the residential energy consumption is estimated.
- Archetypes—This technique is used to broadly classify the housing stock according to vintage, size, house type, etcetera. It is possible to develop archetype definitions for each major class of house and utilize these descriptions as the input data for energy modeling. The energy consumption estimates of modeled archetypes are scaled up to be representative of the regional or national housing stock by multiplying the results by the number of houses which fit the description of each archetype.
- Sample—This technique refers to the use of actual sample house data as the input information to the model. This allows for the capture of the wide variety of houses within the stock and can be used to identify regions with high-energy consumption. If the sample is representative of the regional or national housing stock, the stock energy consumption can be estimated by applying appropriate weightings to the results. As the variety of houses varies widely, this technique requires a large database of representative dwellings.

5.2.1. Distributions

EM models can be constructed by using regional or national distributions of appliance ownership and use, and determining the end-use energy consumption. While they rely on national assessments of appliance penetration and can incorporate historic energy consumption, their level of disaggregation (by end-use)

allows them to be considered bottom-up. As the number of houses and appliance penetration distributions are known, the resultant energy consumption is considered to be representative of the region or nation.Capaso et al. [56] developed an appliance use profile of the Italian residential sector based on distributions determined from housing surveys. Demographic and lifestyle data combined with engineering data of a wide range of appliances was used to calculate total house energy consumption. Their model was applied to the region and compared well with load recordings.

Jaccard and Baille [57] developed a model of Canadian provinces using the INSTRUM-R simulation tool. The inputs to the model include historic energy consumption, price, behavioural parameters, distribution levels of technologies, and quantification of appliance unit energy consumption, cost, and availability. The simulation tool then explicitly models the energy consumption of each appliance, the sum of which is considered to be the residential energy consumption. Functions are included to retire old housing stock and also to test the housing stock for retrofit potential. Based on the potential it simulates the purchase of new appliances. The authors detail the advanced life cycle cost assessment features of the model which do not assume perfect knowledge across space and time, thereby limiting a single technology capturing 100% of the market. They consider this to be a strong asset of the model as it more appropriately simulates the regional technology choices.

Using a combination of distributions and micro-level data sources, Kadian et al. [58] developed an energy consumption model of the residential sector of Delhi. They used a simplified end-use consumption equation to incorporate the penetration and use factors of all households, similar to Eq. (1) although extended to individual end-uses. They included end-uses such as lighting, water heating, air conditioning, refrigeration, cooking, washing, and certain subjective loads. The sum of the end-use energy consumption was input into the long range energy alternatives planning (LEAP) system to incorporate variables such as population, income, and increasing number of houses.

Saidur et al. [1] created a non-space heat residential energy model of Malaysia based on different researchers' distribution estimates of appliance ownership, appliance power rating and efficiency, and appliance use (there is no SH requirement in Malaysia). Their estimate of national annual energy consumption is the summation of the product of each appliance's variables and reciprocal of efficiency. Furthermore, they conducted an exergy analysis to complement their efficiency analysis. The exergy analysis allowed for a comparative tool by which to gauge different energy sources and conversion devices based on a reference state. They found an overall energy efficiency of 69% and exergy efficiency of 30% for Malaysia, as shown in Table 2. They state the gap in efficiencies is due to a mismatch of input and output quality levels (i.e. high temperature energy resources were used for low temperature applications). This is dominated by the refrigerator and air conditioner.

Table 2
Overall energy and exergy efficiency of the residential sector [1].

Country	Year	Overall energy eff.	Overall exergy eff.
China	2005	–	10
Canada	1986	50	15
USA	1970	50	14
Brazil	2001	35	23
Italy	1990	–	2
Japan	1985	–	3
Sweden	1994	–	13
Turkey	2004–2005	81	22
Norway	2000	–	12
Saudi Arabia	2004	76	9
Malaysia	2004	70	29

5.2.2. Archetypes

The EM can be applied to a limited set of dwellings that represent classes of houses found in the residential sector, commonly referred to as "archetypes". Depending on the level of detail, modeling of archetypes can capture the interconnectivity of appliances and end-uses within the house which is not possible using models based on distributions. Parekh [59] describes the process of developing archetypes for energy simulation. The author outlines three basic criteria in generating archetypes: geometric characteristics, thermal characteristics, and operating parameters. Using housing surveys and available housing data, geometric and thermal characteristics are correlated to arrive at various groupings found within the housing stock. Data from these archetype groups was examined for minimum, average, and maximum values for use in determining representative characteristics of each archetype for use with building simulation programs.

As the archetype modeling method typically involves a highly detailed integrated simulation of a house, its development progressed with computer and software capabilities. As the number of archetypes is limited, they are the input of choice for EM models as they reduce simulation time as compared with the sample technique which models each house within a database.

MacGregor et al. [60] developed the Nova Scotia residential energy model using three insulation/infiltration levels and nine dwelling types, resulting in 27 archetypes. They used typical values of occupancy, appliances and lights, and evaluated the energy consumption of each archetype using the hourly analysis program (HAP) developed by Carrier Corporation [61]. Energy consumption values were extrapolated to provincial levels based on the estimated number of dwellings represented by each archetype. The results were found to be in agreement with regional top down estimates. The model was used to evaluate the potential for energy savings and economic benefits of introducing small-scale fluidized-bed furnaces for residential space and DHW heating.

Kohler et al. [62] developed a mass, energy, and monetary flow model of the German building sector. They recognized the building stock as the largest economic, physical, and cultural capital of industrialized countries, although the stock is not yet well quantified. To overcome this lack of data, they decomposed survey data into basic elements and classed them. While they state they are "reference" buildings and not "typical", they are associated with "age-use" classifications characteristic of archetypes. Each group was broken down into detailed elements such as window type. Using these elements they developed building specifications which comprise the materials and operations with respect to the building. Included in their model was retirement and replacement of both buildings and appliances. The authors found their bottom-up model was in agreement with other studies and energy surveys.

Huang and Broderick [63] developed an EM model of space heating and cooling loads of the American building stock using 16 multifamily and 45 single-family "prototypical" residential buildings. These archetypes were simulated in 16 different regions; some archetypes were simulated in as many as six regions. The authors utilized DOE-2.1, a building energy simulation program supported by the USA Department of Energy [64]. Building heating and cooling loads were disaggregated to show the contributions from the walls, roof, windows, infiltration, and internal gains by setting the thermal conductivity of each component to zero. They also included plant efficiencies, accounting for part-load efficiency and air-conditioner efficiency; however, only furnace/air-conditioner plants were modeled owing to the source of the archetypes from the Gas Research Institute. The authors utilized building population estimates provided by [8] to scale their results up to a national value. This was accomplished by normalizing the archetypes' energy consumption by heated floor area and multiplying by the national floor area value.

Jones et al. [65] developed an energy and environmental prediction model which utilized GIS techniques. They used a unique technique that augments archetypes with additional information based on a "drive-pass" survey. The model employs the UK Standard Assessment Procedure to simulate a dwelling based on building fabric, glazing, ventilation, water heating, space heating, and fuel costs. To reduce information collection time and effort, residences with similar characteristics were grouped and modeled by an archetype. The augmentation process was accomplished by using GIS to estimate building area, historical sources to estimate age, and the drive-pass (the process of assessing building characteristics from the sidewalk) to determine storeys, chimneys, and the ratio of window to wall area.

Using the developed archetypes (five age groups and twenty built forms) augmented with individual characteristics, the authors simulated the energy consumption of each dwelling in Neath Port Talbot, UK. Using GIS they illustrate the high consumption areas and those dwellings which have high potential for upgrades, as shown in Fig. 6.

Shipley et al. [66] developed archetypes of different Canadian government building types to represent over 3500 buildings. The archetypes were based on categories such as type, floor area, and age. They developed the commercial energy and emissions analysis model which utilizes ASHRAE's modified bin method, which is described by [67]. Archetypes reduced their simulation efforts as the average building accounted for the large group of diverse buildings. They calibrated the model using supplied energy consumption information from a subset of the buildings and used the model to determine the impacts of building envelope improvements.

Carlo et al. [68] took a different approach to the development of archetypes to represent Brazilian commercial buildings. Using previous simulation results of 512 buildings, the authors determined the primary variables of a building energy regression equation to be roof area ratio, façade area ratio, and internal load density. Combinations of these variables were used to develop 12 archetypes which were augmented with additional variables for parametric simulation. This resulted in 695 prototype buildings which were simulated in DOE-2.1 to determine their energy consumption. The results were used in the assessment of potential building code changes.

Shimoda et al. [69] developed a residential end-use energy consumption model on the city scale for Osaka, Japan. They developed 20 dwelling types and 23 household (occupant) types to represent the variety of houses within the city. Each dwelling type (not detailed in the paper) was modeled using conductive heat transfer analysis; however, each dwelling was considered to have identical insulation levels based on 1997 commercial offerings. This identical insulation level is a major drawback. Households were developed based on the number of family members, appliance ownership levels, and appliance ratings. Each archetype was simulated and multiplied by the number of dwellings it represents. The authors found two interesting results from their technique: the total estimated residential energy use is less than historical values because "unreasonable" energy use (e.g. leaving lights on) was not accounted for, and estimated unit energy consumption is larger than statistical values which they attribute to surveys focusing on larger families.

Wan and Yik [70] took an alternate approach to archetypes and focused on solar gains. After conducting a survey of typical housing characteristics in Hong Kong including floor plan, they developed a single archetype of 40 m^2 floor area with a rectangular living and dining room, two bedrooms, kitchen, and a bathroom. They applied typical characteristics including wall thickness, window to wall ratio, glass thickness and wall absorptivity. To introduce variety, they rearranged the floor plan layout and orientation while maintaining the size and room geometries; this resulted in different window areas facing the sun. In addition they specified different family types and use profiles. They utilized HTB2 (heat-transfer) and BECRES (air-conditioning) simulation engines described by [71,72]. They found their estimates of air conditioner energy consumption to be large when compared to historical statistics and they decreased this difference by reducing appliance usage and ownership level within the dwellings. After the modification the predicted energy consumption compared well with statistics.

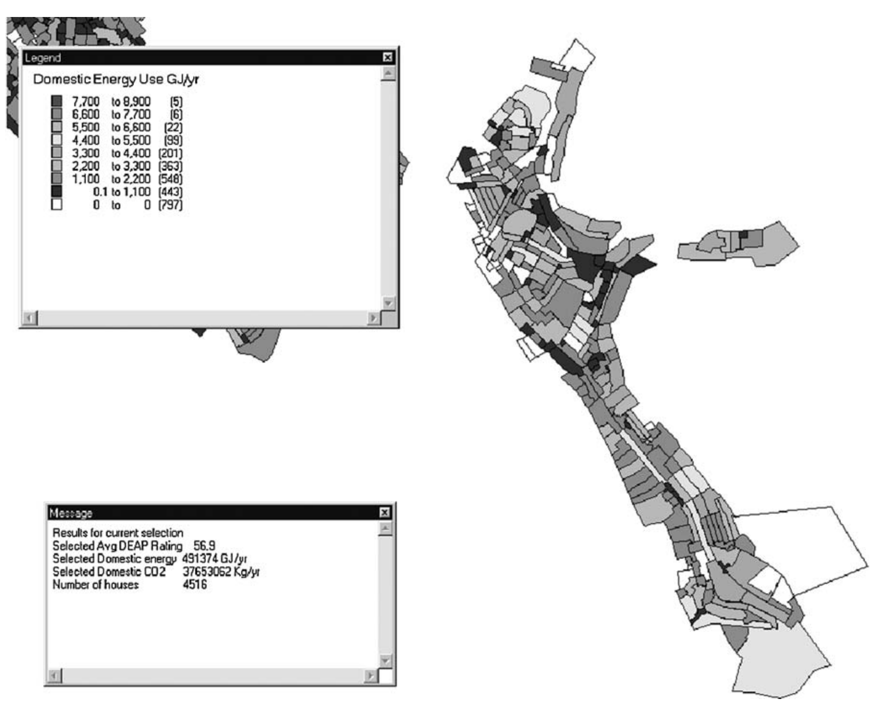

Fig. 6. Domestic energy intensity of individual residences in Neath Port Talbot [65].

Yao and Steemers [73] developed a model based on four typical UK housing topologies: flat, semi-detached, detached, and mid-terraced. Using national appliance ownership distributions, average appliance use, and average appliance rating, the authors generated random daily aggregate appliance energy consumption profiles. They used the thermal resistance method developed by the Martin Centre to calculate heating losses. They generated a regional profile based on 100 generated households and found it to be in agreement with national statistical data.

Palmer et al. [74] developed a model of the UK housing stock using 431 archetypes. They used the BREDEM-8 Building Research Establishment tool which is a monthly heat flux simulation program to model the required SH and DHW heating energy consumption [75]. Occupant and appliance heat gains are calculated based on distributions and DHW consumption is based on typical values. Their model encompasses trends of construction/demolition and demographic changes to estimate the energy consumption of the residential sector through 2050.

Petersdorff et al. [76] modeled the EU-15 building stock by examining five standard buildings with eight insulation standards. They used Ecofys's built environment analysis model (BEAM) to calculate the heating demand for three climatic regions. The three house types included in the model were terrace, small apartment, and large apartment. The eight insulation standards applied to the buildings were determined based on typical values for the climatic conditions and building vintage found in EU countries. The authors modeled different scenarios of retrofit and construction/demolition, and attempted to extend the model to smaller housing types. They found their models corresponded well with statistical data.

To extend the archetype methodology beyond its typical position of limited variety, Nishio and Asano [77] developed an archetype generation tool based on the Monte-Carlo technique. The authors utilized numerous statistics, surveys, and conventional datasets from Japan to define both the distribution and range of housing variables. Their house generator uses the Monte-Carlo technique to define attributes for each archetype based on probability assumptions. It then develops hourly patterns of energy consumption for common activities, and aggregates and applies these on a monthly basis as a function of the proposed family composition. While the number of generated houses is variable, the generator relies on 34 different family types and 47 different climatic regions. In an example, they generate and analyze 10,000 houses.

Clarke et al. [78] focused on the main determinants of energy demand within the Scottish building stock to create representative thermodynamic classes. Using the following determinants and their value or level, they developed 3240 classes: insulation level (6), capacity level (2), capacity position (3), air permeability (3), window size (3), exposure (5), and wall to floor area ratio (2). Each class was modeled using the building performance simulation software ESP-r to determine the thermal energy requirements of the dwelling [79]. System information such as heating/cooling, ventilation, DHW, and lighting was then applied to calculate the total energy consumption of the dwelling. The results were incorporated into a tool for comparative analysis and assessment of the impact of improvement measures upon the stock.

5.2.3. Samples

While archetypes provide a limited representation of the regional or national housing stock due to the limited variety of archetypes that can reasonably be defined, the use of actual house samples with the EM can realistically reflect the high degree of variety found in the actual housing stock, provided that the sample size is sufficiently large. As this form of EM modeling is data intensive, its application has been limited.

Farahbakhsh et al. [80] developed a model of the Canadian housing stock based on 16 archetypes augmented with data from 8767 actual houses. As the house data came from a national housing survey database that is statistically representative of the Canadian housing stock, weights of house representation were provided for the purpose of scaling the consumption up to provincial and national values. An individual house input file was generated for each of the 8767 houses and simulated using Natural Resources Canada's HOT2000 monthly bin type building simulation software [81]. As energy billing data was available for 2524 houses, these were used in the calibration procedure to correct data conversion errors in the input files. The national consumption estimate was found to be in agreement with other studies. Using this national residential energy model, Guler et al. [82,83] studied the impact and economic analysis of energy efficiency upgrades on energy consumption and greenhouse gas emissions. They found energy savings and greenhouse gas reduction potential for upgrades of heating systems to be 8%, basement insulation to be 4%, and programmable thermostats to be 2% (approximate values reported here). Using the energy costs at that time, the major upgrades were not found to be economically feasible. Aydinalp et al. [84] updated the model of [80] by using housing data from 1997 and found that the UEC had increased by 1.8%.

Larsen and Nesbakken [85] developed a model of Norway's housing stock using household information from 2013 dwellings. They describe the simulation engine, ERÅD, and identify its fundamental weakness as the high number of numerical inputs. Significant efforts were required to calibrate the model which is not desirable as the engineering technique should calculate appropriate initial values. They note that while it is possible to account for every end-use in an engineering model, unspecified end-uses must be estimated. Instead, this was accounted for by calibrating the known end-uses, resulting in a slight overestimate of each end-use contribution. The authors found SH and DHW to be approximately 42% and 24% of total consumption, respectively.

Two other sample EM models deal with commercial buildings. Ramirez et al. [86] modeled 2800 commercial premises of California using a modified version of eQuest building simulation software [87]. Combining survey information from all 2800 buildings, their energy billing data, sub-metered data from 500 buildings, and current year weather data from 20 stations, the authors modified predefined footprint templates to represent each building. The model numerically and visually displayed the hourly results of each building simulation. Calibration was conducted on each building model by a simulation specialist and consisted mainly of verifying significant end-uses and their ranges. Final alterations were made by adjusting schedules and operating hours. During the calibration process it was found that occupation, or lack thereof, of the building has unexpected impacts. Specifically, the assumption that AL is turned off at the end of the business day was found to be false.

Griffith and Crawley [88] developed a similar model. They modeled 5430 buildings that comprise the Commercial Buildings Energy Consumption Survey Database (CBECS) and included weighting factors for extrapolation to national results for the USA. However, their focus was the "technical potential" of the sector (i.e. the lowest feasible energy consumption) and thus the 2005 building code requirements were applied to each building. Additional information not included in the CBECS was developed using ASHRAE standards and pseudo-random application of average parameter distributions, such as infiltration. They developed a rule based pre-processor to translate the parameters into "shoebox" building input files for simulation by the USA Department of Energy's EnergyPlus software [89]. Simulations were conducted on a computer cluster. They determined that the high number of building records was a disadvantage as it required

significant computing capability. They recommend this technique only when results must reflect national implications on a limited number of scenarios. They recommend a smaller database size for high numbers of parametric simulations.

Swan et al. [90] is developing a national residential energy model of Canada using a detailed database of nearly 17,000 houses. The housing database, described by [12], is a selected subset from a national home energy audit program database that characterised the thermal envelope of each dwelling, including an air tightness test. The database of houses descriptions is presently being converted to detailed house models for building energy simulation using the software ESP-r [79]. The detailed house descriptions and high-resolution simulation (one hour time-step) allow for an assessment of the impact on energy consumption due to the application of new technologies to appropriate houses.

6. Critical analysis of top-down and bottom-up approaches

The top-down and bottom-up approaches each have distinct similarities and differences, as well as advantages and disadvantages. Two of the most critical issues that characterize these approaches are the required input information and the desired range of modeled scenarios.

6.1. Strengths and weaknesses of the top-down approach

Top-down approaches are relatively easy to develop based on the limited information provided by macroeconomic indicators such as price and income, technology development pace, and climate. Top-down models heavily weigh the historical energy consumption which is indicative of the expected pace of change with regards to energy consumption. This weighting may be seen in Eq. (4). Models that evaluate from a regional or national scope are useful for estimating the required energy supply and the implications of a changing economy. They falter when discontinuity is encountered. Examples of such situations include technological breakthroughs or severe supply shocks, the latter being most pronounced due to the slow turnover rate of the housing stock. Contrary to other studies and with respect to a practical sense given today's energy environment, Haas and Schipper [18] clearly identified non-elastic response due to "irreversible improvements in technical efficiency". This exemplifies the importance of including a representative technological component in top-down models. Jaccard and Bailie [57] discussed the notable dichotomy that top-down models estimate high abatement costs for reducing carbon dioxide emissions whereas bottom-up models' estimates are notably lower. They attribute this to economists' over-reliance on the autonomous energy efficiency index (AEEI) and the elasticity of substitution (ESUB). The NEMS has included both a *technology* and *distributed-generation* component [24]. This indicates that top-down modeling systems are now attempting to account for the uptake of new technologies. While these techniques may account for future technology penetration based on historic rates of change, they do not provide an indication of the *potential* impacts of such technologies and are therefore not helpful in the development of policy or incentive to encourage them.

6.2. Strengths and weaknesses of the bottom-up approach

Bottom-up statistical techniques bridge the gap between detailed bottom-up end-use energy consumption models and regional or national econometric indicators. These techniques are capable of encompassing the affects of regional or national economic changes while indicating the energy intensity of particular end-uses. The primary information source of the bottom-up SM is energy supplier billing data. While this is private information, the sheer quantity and quality of this information warrants further compilation and use. By disaggregating measured energy consumption among end-uses, occupant behaviour can be accounted for. This is a distinct advantage of the SM over the EM. Of the three bottom-up SM techniques, common regression is the least favoured as the utilized inputs vary widely among models, limiting their comparison. In contrast, CDA is focused on simplifications of end-uses and is therefore easily ported to other locations and its predictions are comparable among different studies. As appliances currently on the market vary widely in size and less in technology, the addition of such information could be beneficial for future CDA studies. Although the NN technique allows for the most variation and integration between end-uses, resulting in the highest prediction capabilities (Aydinalp et al. [91]), its coefficients have no physical significance. This is a severe drawback. Estimation of individual end-uses was demonstrated by removing their presence in the NN model. However, due to the interconnectivity between each end-use, the removal of many end-uses, individually or simultaneously, reduces the level of confidence in the resulting predictions. Furthermore, bias of the energy estimation error was found when using the NN technique. Aydinalp-Koksal and Ugursal [47] provide a detailed review and comparison of specific CDA, NN, and EM models.

Bottom-up EM techniques rely on more detailed housing information. These models explicitly calculate or simulate the energy consumption and do not rely on historical values, although historical data can be used for calibration. Larsen and Nesbakken [85] developed both engineering (samples) and statistical (CDA) models to compare their results. They noted that the engineering technique requires many more inputs and has difficulty estimating the unspecified loads, but while the statistical technique reduces both of these issues it is hampered by multicollinearity resulting in poor prediction of certain end-uses.

If the objective is to evaluate the impact of new technologies, the only option is to use bottom-up EM techniques. This is a point of emphasis because compared to taxation and pricing policies, technological solutions are more likely to gain public acceptance to reduce energy consumption and the associated greenhouse gas emissions. The EM is capable of modeling on-site energy collection or generation such as active or passive solar and co-generation technologies.

The most apparent drawback of the EM is the assumption of occupant behaviour. Because the effect of occupant behaviour can significantly impact energy consumption, the assumption of occupants' activities is not trivial. Statistical techniques based on monthly data are capable of incorporating the effects of occupant behaviour, although they may be inappropriately applied to end-uses. Also, the high level of expertise required in the development and use of the EM may be considered a drawback. The computational limitations discussed by Griffith and Crawley [88] regarding large numbers of simulations are no longer critical as the data processing capability of computers is continuing to increase rapidly.

To address the shortcomings of both the EM and the statistical based models, research is currently being conducted by Swan et al. [90] to develop a "hybrid" EM and NN model for the Canadian housing sector that will incorporate a NN model to predict the highly occupant sensitive DHW and AL energy consumption, while using the EM to predict the SH and SC energy consumption.

6.3. Attributes and applicability of the modeling approaches

The important attributes of the three major residential energy modeling approaches, namely the top-down, bottom-up statistical and bottom-up engineering, are shown in Table 3. Each approach

Table 3
Positive and negative attributes of the three major residential energy modeling approaches.

	Top-down	Bottom-up statistical	Bottom-up engineering
Positive attributes	• Long term forecasting in the absence of any discontinuity	• Encompasses occupant behaviour	• Model new technologies
	• Inclusion of macroeconomic and socioeconomic effects	• Determination of typical end-use energy contribution	• "Ground-up" energy estimation
	• Simple input information	• Inclusion of macroeconomic and socioeconomic effects	• Determination of each end-use energy consumption by type, rating, etc.
	• Encompasses trends	• Uses billing data and simple survey information	• Determination of end-use qualities based on simulation
Negative attributes	• Reliance on historical consumption information	• Multicollinearity	• Assumption of occupant behaviour and unspecified end-uses
	• No explicit representation of end-uses	• Reliance on historical consumption information	• Detailed input information
	• Coarse analysis	• Large survey sample to exploit variety	• Computationally intensive
			• No economic factors

meets a specific need for energy modeling which corresponds to its strongest attribute:

- Top-down approaches are used for supply analysis based on long-term projections of energy demand by accounting for historic response.
- Bottom-up statistical techniques are used to determine the energy demand contribution of end-uses inclusive of behavioural aspects based on data obtained from energy bills and simple surveys.
- Bottom-up engineering techniques are used to explicitly calculate energy consumption of end-uses based on detailed descriptions of a representative set of houses, and these techniques have the capability of determining the impact of new technologies.

Given today's energy considerations that encompass supply, efficient use, and effects of energy consumption leading to the promotion of conservation, efficiency, and technology implementation, all three modeling approaches are useful. Top-down models are the clear winner in supply considerations as they are heavily weighted by historical energy consumption which places their estimates of supply within reason. Bottom-up statistical models can account for occupant behaviour and use of major appliances, which leads to the identification of behaviours and end-uses which cause consumption of unwarranted quantities of energy. Lastly, bottom-up engineering models may identify the impact of new technologies based on their characteristics and account for the wide degree of variety within the housing stock.

As the effects and limitations of conventional energy sources (i.e. fossil fuels) are widely acknowledged, alternative energy sources and technologies are continuously being investigated and developed. To determine the impacts of such new developments requires a bottom-up model. This is further exemplified by the focus being placed on efficiency and on-site energy collection and generation at individual houses. During this period of rapid technological development and implementation, the bottom-up techniques will likely provide much utility as policy and strategy development tools.

Acknowledgements

The authors gratefully acknowledge the financial support provided to this project through the Solar Buildings Research Network primarily funded by the Natural Sciences and Engineering Research Council of Canada (NSERC), as well as through the Discovery Grant provided to V.I. Ugursal by NSERC.

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